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How Review Sentiment and Readability Affect Online Peer Evaluation Votes? – An Examination Combining Reviewer’s Social Identity and Social network

Abstract: To encourage users’ engagement and crowdsource quality control, many online communities provide users with peer evaluation votes. By using a total number of 17,178 online hotel reviews from Yelp, this study explored the factors influencing hotel review peer evaluations. The empirical results show that (1) multiple motivations exist for peer evaluations of online reviews; (2) except for reviews’ post date, length, and hotel popularity, readability of hotel review has positive influences on evaluation votes; (3) review sentiment has stronger influences on evaluation votes than other factors; (4) the effects of hotel review sentiment and readability on peer evaluation votes are positively moderated by reviewer’s social identity and social network.

Keywords: peer evaluation; review readability; review sentiment; social identity; social network

Introduction

With the proliferation of Internet use, online reviews have become an important information source of consumer experience towards products and of word-of-mouth. Some online communities providing consumer reviews, including Yelp and Tripadvisor, have become extremely popular (Liu and Park 2015).

Given the importance of online reviews, how to engage online users to write more valuable reviews is an important theme and research topic. Many online community studies focus on the users' motivation to voluntarily contribute when there is no monetary return (Bateman, Gray and Butler 2011; Ma and Agarwal 2007; Wasko and Faraj 2005). In particular, Wasko and Faraj (2005) find that reputation seeking motivations and structural embeddedness are two important motivations for users to contribute. Similarly, Bakhshi, Kanuparth, and Shamma (2015) argue that peer evaluation is commonly used to enhance online user engagement. According to the reciprocity, reinforcement, and need to belong theories, fellow members' feedback could enhance and predict the future and long-term participation behavior for a user.

Therefore, to encourage content generation, users' engagement with the site and crowdsource quality control, many online communities provide users with voting and feedback system similar to a form of peer evaluation (Bakhshi, Kanuparth and Shamma 2015; Goes, Lin and Au Yeung 2014). These feedback systems enable online users to generate social signals in the community, such as review's "helpful" votes in Amazon and Tripadvisor, "like" votes in Facebook, and Twitter. In addition, the online review website Yelp divides the above mentioned one kind of feedback into three different feedback signals as "useful", "cool" or "funny", or different combinations of the three different votes. This practice brings more varieties of social feedback signals. The bigger variety of feedback signals in Yelp could also encourage online users to interact with the review content and other users in a more interesting and meaningful way, and eventually generate more interactions and contributions.

On this basis, by examining online hotel review data from Yelp, this study aims to explore how social feedback regarding the review characteristics such as readability and sentiment contributes to the peer evaluation, and to better understand the moderating effects of reviewer's social identity and social network on peer evaluation of online reviews. The study will lead to a research direction to better understand different user feedback social signals and social network so as to motivate online user engagement and to design better online recommendation system.

Literature Review

Review Sentiment

Most of previous studies use the review star ratings as a proxy for review sentiment (Liu and Park 2015; Fang, Ye, Kucukusta, and Law 2016), although there are some discrepancies. Wei, Miao, and Huang (2013) report that reviews with higher hotel numeric ratings are more likely to be voted as more helpful than those with lower numeric ratings. Compared to negative online reviews, positive are consistent with and validate customers' predecisional interest, so they are perceived more helpful (Wei, Miao and Huang 2013). However, other researchers, such as Danescu-Niculescu-Mizil, Kossinets, Kleinberg, and Lee (2009) demonstrate that online consumers usually perceive extreme reviews, either positive (five-star ratings) or negative (one-star ratings), more useful than reviews with moderate star ratings (three-star ratings). Extreme sentiment could be either unexpectedly exciting or disappointing, thus speeches with extreme

sentiment will be more persuasive (Nabi 1999). Positive and negative reviews that reflect the specific reasons and experiences enable audiences to reflect better as they resemble the stories in their memories (Park and Nicolau 2015). On this basis, we propose the following hypothesis:

Hypothesis 1: Review sentiment has significant influence on peer evaluation, with stronger effects for reviews with extreme positive or negative sentiment.

Review Readability

Online reviews are important information sources that consumers use to know about products or services. As one of the quantifiable metrics of texts, readability, which is judged by its writing style, refers to how easily the text could be understood by readers (Klare 1974). According to Fang, Ye, Kucukusta, and Law (2016), written reviews with high readability are considered more reliable or credible than those with low readability. When the review is precise or easy to understand, it spreads to more people. On this basis, we propose the following hypothesis:

Hypothesis 2: Review readability has a positive influence on peer evaluation.

The moderating effect of user's social identity

Social identity refers to “individuals’ definition of the self in terms of group-defining attributes” (Forman, Ghose and Wiesenfeld 2008, p. 293). Social identity theory indicates that “identification” is a critical element of the psychological basis of people’s engagement among their social networks (Blader and Tyler 2009).

Majority of online review websites, such as Yelp and Tripadvisor, have a reviewer credentialing program, in which reviewers could be certified if they have substantially contributed to Yelp. There are two primary criteria for the contribution: (1) the number of reviews; and (2) number of reviews deemed as helpful by Yelp. Reviewers who are marked as “elite” usually write a large number of helpful reviews and “elite” represents a reputation of informative reviews. Moreover, some online review websites allow readers to filter reviews to read online reviews written by elite reviewers only. Based on the consumer reviews on the restaurant industry from Yelp.com, Luca (2011) reports that consumers’ response to a restaurant’s average rating is affected by the number of reviews and whether the reviewers are certified as “elite” by Yelp. The results further show that elite reviewers have roughly double the impact of other reviewers. On this basis, we propose the following hypothesis:

Hypothesis 3: Reviewer’s social identity moderates the effects of review characteristics, such as the sentiment and readability, on peer evaluation.

The moderating effect of social network

Pfeil, Arjan, and Zaphiris (2009) report that user-generated-content (UGC) is flourishing on online social networks with many strong and weak ties involved. Goes, Lin, and Au Yeung (2014) argue that more websites are becoming social-oriented so that users connect to each other more easily and therefore have more peer influence than before. Currently, online review websites strategically enhance users’ interactions by allowing users to stay connected and become “friends”. There are three reasons that reviewer’s social network may moderate the

effect of review text characteristics on peer evaluation votes, including the “web-of-trust” feature, social influence and preference similarity, and exposure priority of online friends.

First, what makes the website interesting is the “web-of-trust” feature (Goes, Lin and Au Yeung 2014). Some online review communities, such as Yelp and Tripadvisor, allow users to form online connections, named “friends” and “fans/followers” with other reviewers, and users can read friends’ reviews conveniently by clicking “friends” button. According to a survey by AC Nielsen in 2012, it was found that consumers think that opinions from friends are the most trustable, while online consumer reviews are second. Therefore, people believe friends more than anonymous online review, and the reviewer who has more friends is more likely to get more peer evaluation votes.

Second, social influence and preference similarity. As Goes, Lin, and Au Yeung (2014) stated that existing empirical studies on social influence in information systems have shown one person’s behaviors influence another if they are connected with each other. As examples, the studies of Aral et al. (2009) and Iyengar et al. (2011) found peer’s behavior influences products and services adoption. Therefore, people who are friends are more likely to influence each other and finally have similar preference, thus the reviewer who has more friends is more likely to get more peer evaluation votes.

Third, the reviews written by online friends has the priority to be exposed. There are two ways. First, when a reader subscribes to a reviewer or they are online friends, content generated by that reviewer will have priority over other reviewers when displayed to the reader as users can read friends’ reviews conveniently by clicking “friends” button. Second, once such a tie is created (friends or followers), if a user searches for information about a product that his/her friends had written a review for, friends’ reviews for that product will be displayed to the user ahead of other reviews.

On this basis, we propose the following hypothesis:

Hypothesis 4: Reviewer’s social network moderates the effects of review characteristics, such as the sentiment and readability, on peer evaluation.

Motivations for Peer Evaluation Votes

Motivation theory suggest two categories of motivations when people perform an activity: (1) extrinsic motivation which relates to goal-driven reasons; and (2) intrinsic motivations with pleasure and inherent satisfaction reasons for its own sake (Ryan and Deci 2000). Park and Nicolau’s (2015) empirical study find that online travelers are more likely to pursue reviews that not only provide useful information for decision-making but also give them enjoyment and fun when reading other travelers’ experiences. Therefore, there are multiple reasons for a review deemed as valuable. In order to increase the peer evaluation and the interaction between the user and reviewer, some online communities provide more peer evaluation social signals. For example, Yelp includes “funny”, “cool”, and “useful” votes, as these different votes are not whimsical signals to increase readers’ click involvement, but actually express other social meanings (Bakhshi, Kanuparth and Shamma, 2015; Park and Nicolau 2015; Bakhshi, Kanuparth and Shamma, 2014).

Based on the literature discussion above, we propose the following research framework:

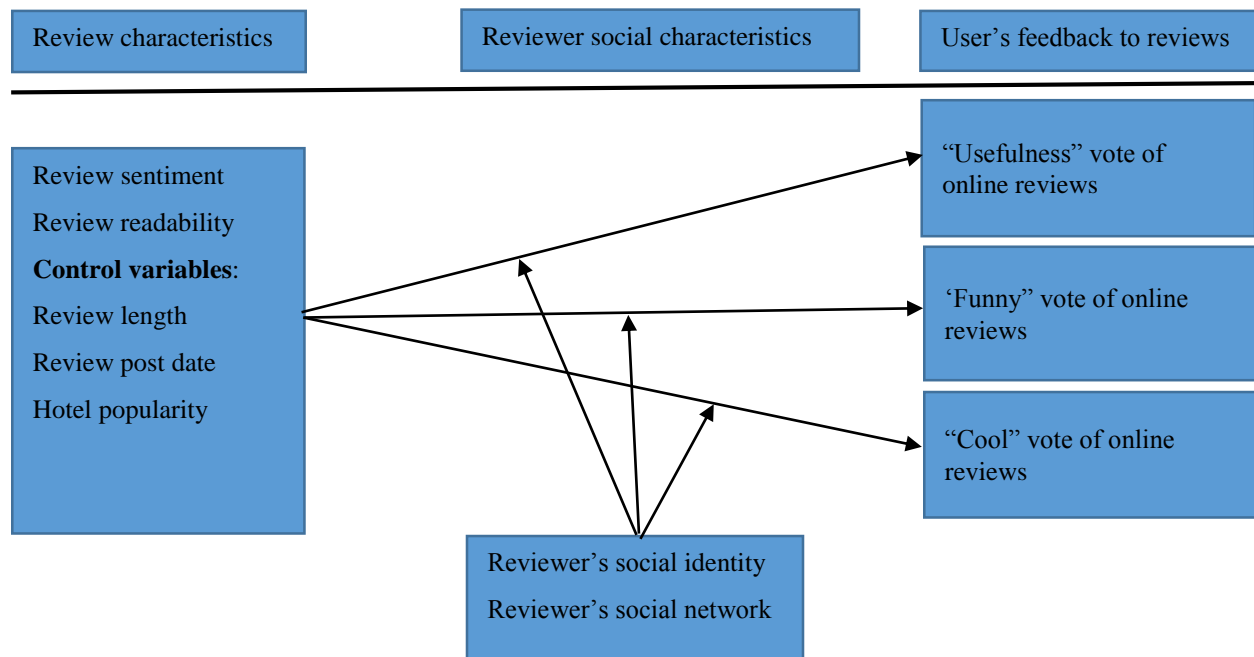


Figure 1. Research Framework

Methodology

Data

This study analyzed the hotel online review data. Ten hotels with the highest number of online reviews in Las Vegas are selected, with a total number of 17,178 online reviews. The data come from one of the biggest online review communities, Yelp, which specializes in online reviews of restaurants, hotels, doctors, and other businesses. Reviewers are requested to provide numerical ratings on a 5-star scale as well as detailed comments on their experience. Moreover, a reviewer's information, such as the reviewer's status, the number of reviews written by the reviewer, and number of friends, are also provided next to the reviewer's user name, which can be seen when users read the reviewer's online reviews. The Yelp user is assigned an "Elite" status by the website, which indicates that the reviewer is more experienced and more likely to be perceived as an expert.

Variable Measurements

The online reviews on Yelp can be voted as cool, funny or useful, or different combinations. These vote counts are used in this study as a measure of peer evaluation. In order to explore the effects of review text on peer evaluation, we analyze each online review on Yelp to quantify the sentiment and readability. Reviewer identity is measured by the number of times the elite titles were certified to the reviewer. The reviewer's social network is measured by the number of online friends the reviewer has in Yelp. In addition, other factors deemed important in previous

literature were also included in the model, including review length, review post date, and the hotel popularity. The measurement of each variable in this study is listed in Table 1.

Table 1. Variable Description

Variable	Description
Dependent variables	
Useful Vote	Number of “useful” votes received by a review
Funny Vote	Number of “funny” votes received by a review
Cool Vote	Number of “cool” votes received by a review
Independent variables	
Readability	Gunning-Fog Index readability index of the review text
Sentiment	Sentiment index of the review text
Date	Number of days elapsed from the review post date
Length	Total number of words in a review
Popularity	Number of total reviews received by a specific hotel
Moderators	
Reviewer’s social identity	Number of times the reviewer achieved the Elite title in Yelp.com
Reviewer’s social network	Number of friends the reviewer has

Sentiment Analysis

In prior hospitality and tourism literature, star ratings is used as a proxy of review sentiment. For the first time, this study calculates the review sentiment by Naïve Bayesian Algorithm (McCallum and Nigam 1998), which is commonly used in text categorization. It uses the joint probabilities of words and categories to estimate the probabilities of categories given a document. Our main aim is to classify the hotel online reviews into the valence categories based on the input training set of the lexical words. The values of the sentiment range from -1 to 1, with range from 0 to 1 meaning positive experience while -1 to 0 meaning negative experience. Moreover, the bigger of the positive sentiment value, the more positive of the experience, while the smaller of the negative sentiment value, the more negative of the experience.

Readability Analysis

The following equation is used to calculate the Gunning-Fog Index (FOG) (Gunning, 1969) readability index:

$$FOG = 0.4 \times \left(\frac{\text{Number of Words}}{\text{Number of Sentences}} \right) + 100 \times \frac{\text{Number of Complex Words}}{\text{Number of Words}}$$

In the above equation, complex word is the word having more than two syllables. The score of FOG index ranges from 1–12, indicating the required educational grade level to understand the review text. The lower the grade, the more readable the text.

Model and Estimation

As the number of peer evaluations is a count variable, this study clearly adopted a count data model. One typical count data model is the Poisson regression model, which assumes that the dependent variable is drawn by a Poisson process. However, the Poisson process requires the mean to be equal to the variance. Since the variance exceeded the mean of the count data in this study, this over-dispersion problem requires us to apply extended models of Poisson regression. Therefore, negative binomial regression 2 model (Cameron and Trivedi 2005, P.675-676) is introduced.

The negative binomial distribution is as follows:

$$h(y|\mu, \alpha) = \frac{\Gamma(\alpha^{-1}+y)}{\Gamma(\alpha^{-1})\Gamma(y+1)} \left(\frac{\alpha^{-1}}{\alpha^{-1}+\mu}\right)^{\alpha^{-1}} \left(\frac{\mu}{\mu+\alpha^{-1}}\right)^y \quad (1)$$

Negative binomial distribution flows:

$$\begin{aligned} E[y|\mu, \alpha] &= \mu \\ V[y|\mu, \alpha] &= \mu(1 + \alpha\mu) \end{aligned} \quad (2)$$

In the above equations, variant μ is specified as $\mu_i = \exp(\mathbf{x}_i\beta)$. . In this study, the following models (3)-(5) are specified:

$$\begin{aligned} \mu_{1ijk} = \exp(&\beta_{10} + \beta_{11}\text{Readability}_{ijk} + \beta_{12}\text{Sentiment}_{ijk} + \beta_{13}\text{Readability}_{ijk} * \text{Elite}_j + \beta_{14}\text{Sentiment}_{ijk} * \\ &\text{Elite}_j + \beta_{15}\text{Readability}_{ijk} * \text{Friends}_j + \beta_{16}\text{Sentiment}_{ijk} * \text{Friends}_j + \beta_{17}\text{Date}_{ijk} + \beta_{18}\text{Length}_{ijk} + \\ &\beta_{19}\text{Popularity}_k + \varepsilon_{1i}) \end{aligned} \quad (3)$$

$$\begin{aligned} \mu_{2ijk} = \exp(&\beta_{20} + \beta_{21}\text{Readability}_{ijk} + \beta_{22}\text{Sentiment}_{ijk} + \beta_{23}\text{Readability}_{ijk} * \text{Elite}_j + \beta_{24}\text{Sentiment}_{ijk} * \\ &\text{Elite}_j + \beta_{25}\text{Readability}_{ijk} * \text{Friends}_j + \beta_{26}\text{Sentiment}_{ijk} * \text{Friends}_j + \beta_{27}\text{Date}_{ijk} + \beta_{28}\text{Length}_{ijk} + \\ &\beta_{29}\text{Popularity}_k + \varepsilon_{2i}) \end{aligned} \quad (4)$$

$$\begin{aligned} \mu_{3ijk} = \exp(&\beta_{30} + \beta_{31}\text{Readability}_{ijk} + \beta_{32}\text{Sentiment}_{ijk} + \beta_{33}\text{Readability}_{ijk} * \text{Elite}_j + \beta_{34}\text{Sentiment}_{ijk} * \\ &\text{Elite}_j + \beta_{35}\text{Readability}_{ijk} * \text{Friends}_j + \beta_{36}\text{Sentiment}_{ijk} * \text{Friends}_j + \beta_{37}\text{Date}_{ijk} + \beta_{38}\text{Length}_{ijk} + \\ &\beta_{39}\text{Popularity}_k + \varepsilon_{3i}) \end{aligned} \quad (5)$$

Where i means the i th review; j means the j th review who writes the i th review; k means the k th hotel; μ_{1ijk} is the mean of number of useful votes; μ_{2ijk} is the mean of number of funny votes; and μ_{3ijk} is the mean of number of cool votes.

Empirical Results

The results for the negative binomial regression 2 model are shown in Table 2. Three different kinds of online peer evaluations are treated as the dependent variables, namely number of funny votes, number of useful votes, and number of cool votes. First, the model specification is examined with hypothesis of dispersion parameter alpha equals to zero (i.e. Poisson regression model). The likelihood-ratio tests show that we reject the null hypothesis, so negative binomial regression 2 models in this study are the correct selection.

Table 2. Empirical Results

	Funny Vote	Useful Vote	Cool Vote
Constant	-1.204198*** (-10.60)	-.716855*** (-9.36)	-2.111596*** (-19.46)
FOG	-.0338544*** (-6.07)	-.0106687*** (-3.00)	-.0377612*** (-6.63)
Sentiment	-.6006476*** (-13.12)	-.5130398*** (-16.75)	.1321135*** (2.85)
FOG×Elite	.0073105*** (4.57)	.0067776*** (6.05)	.0119333*** (7.69)
Sentiment×Elite	.0539799*** (3.18)	.0470585*** (3.96)	.032873** (2.06)
FOG×Friends	.0001602*** (5.27)	.0000735*** (3.71)	.0002016*** (7.50)
Sentiment×Friends	.0019776*** (6.21)	.001871*** (9.01)	.0016149*** (5.84)
Date	.0001889*** (8.63)	2.33e-06 (0.15)	.0002585*** (13.01)
Length	.0023168*** (22.60)	.0024933*** (35.88)	.0019801*** (21.62)
Popularity	.0001339*** (2.84)	.0002103*** (6.66)	.0002658*** (6.17)
Alpha	2.386341	1.02028	1.544725
Likelihood-ratio test of alpha=0	9669.17 (P=0.000)	7674.26 (P=0.000)	6725.51 (P=0.000)
Log Likelihood	-16287.357	-23481.494	-16121.838
LR Chi2	2656.06 (df=9, P=0.000)	4237.82 (df=9, P=0.000)	3997.29 (df=9, P=0.000)
Pseudo R2	0.0754	0.0828	0.1103
Number of Observations	17178	17178	17178

Note: The values in parentheses indicate the z ratio. The asterisks indicate that the coefficient is significant at the *10%, **5%, and ***1% level.

Table 2 shows that all the control variables have the expected signs for the three models. Number of days elapsed from the review post date (Date) has a positive effect on the number of funny, useful and cool votes, although it is not statistically significant for the effect on the useful votes. Total number of words of a review (Length) also demonstrates significant positive effects on the number of funny, useful and cool votes. Number of total reviews received by a specific hotel (Popularity) also show significant positive effects on the number of funny, useful and cool votes, in other words, more reviews for a hotel means more chance of exposure for a specific review.

Specifically, hotel review sentiment has negative influence on funny and useful votes, with coefficients equals to -0.601 and -0.513; while sentiment has positive influence on cool votes, with coefficients equals to 0.132. Therefore, hypothesis 1 is supported that review sentiment has significant influence on peer evaluation, with stronger effects for reviews with extreme sentiment. In addition, the estimation results show that review readability has positive influence on number of funny, useful and cool votes, suggesting hypothesis 2 be supported. A comparison of the magnitude of the coefficients also demonstrates that the sentiment and readability of reviews have stronger influences than other control variables.

Regarding the moderating effect, it was found that reviewer's social identity and social network positively and significantly moderate the influences of hotel reviews' sentiment and readability on peer evaluation, suggesting hypotheses 3 and 4 be supported. Specifically, for "Elite" reviewers, the influence of reviews' sentiment and readability on peer evaluations (the number of votes received) were strengthened. Similarly, for reviewers with stronger network, the influence of reviews' sentiment and readability on peer evaluations were also strengthened.

Conclusion and Implications

This study explored how hotel online review characteristics such as readability and sentiment contribute to peer evaluation votes, as well as the moderating effect of reviewer's social identity and social network. The contributions of this study are two-fold: first, this study is one of the few which empirically support the multiple motivations for online peer evaluation votes; second, this study takes an initial attempt to examine the moderating effects of reviewer's social identity and social network on the relationship between online review characteristics and peer evaluation votes.

Specifically, multiple motivations for online peer evaluation votes are supported to cast useful, funny, and cool votes, and the social meanings for each motivation is explored. Therefore, to encourage content generation and users' engagement with the site, multiple peer feedback votes are suggested to replace only one "useful/helpful" vote.

In addition, for "elite" reviewers and those who have more friends, the sentiment and readability regarding the online reviews have stronger effect on the number of peer evaluation votes. On this basis, social connection and certification system (elite) are recommended in the online review community, so as to increase the number of hotel review feedback votes, which in turn enhance reviewers' online engagement and participation in the future (Bakhshi, Kanuparth and Shamma 2015).

Future study should further analyze the reviewer's social network, dividing the friends into different groups based on their online engagement characteristics, such as monetary value, frequency, and recency (Ngo-Ye and Sinha 2014). Moreover, future research could also examine the influence of peer evaluation/feedback on reviewer's online behavior, including the review writing characteristics as well as social connection. The relationship between reviewer's online behavior and peer evaluation may not be a one-way relationship, therefore it is important to examine the mutual relationship between reviewer's online behavior and peer evaluation.

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